Trust, Explainability, and Workflow Integration of Multimodal AI in Dermatology: Insights from Indian Dermatologists

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Abstract—Multimodal artificial intelligence (AI) has demonstrated substantial diagnostic potential in dermatology, yet its translation into routine Indian clinical practice remains nascent. This cross-sectional survey of 300 practising Indian dermatologists investigates three interrelated constructs: (i) trust in AI-generated diagnoses, (ii) preferences for explainability mechanisms, and (iii) readiness for workflow integration. Findings reveal a bifurcated trust landscape: 84.3% of respondents endorsed AI as a decision-support adjunct, whereas only 38.7% expressed unconditional diagnostic trust. Explainability emerged as the dominant trust mediator—79.0% of participants indicated greater trust when AI outputs were accompanied by visual or textual explanations, with Grad-CAM heatmaps and natural-language rationales identified as the most acceptable formats. Workflow integration lagged substantially: only 29.0% reported current clinical use of AI tools, with inadequate digital infrastructure, absent regulatory frameworks, and paucity of India-representative training data cited as the three highest-ranked systemic barriers. Dermatologists in metro settings and academic institutions demonstrated significantly higher AI familiarity and adoption readiness compared to rural and Tier-3 counterparts. These results underscore the urgent need for India-specific model validation, structured AI literacy curricula, Central Drugs Standard Control Organisation (CDSCO) approval pathways, and interoperable electronic health record (EHR) integration to realise equitable AI deployment in Indian dermatology.

Index Terms—Artificial intelligence, dermatology, explainability, Grad-CAM, India, multimodal AI, skin lesion classification, trust, workflow integration, XAI

I. INTRODUCTION

India carries one of the world's heaviest skin disease burdens. According to the Global Burden of Disease Study 2017, dermatological conditions ranked among the top four non-fatal disease categories in the country, accounting for substantial years lived with disability (YLD) [1]. Notwithstanding this burden, the country faces a severe workforce deficit: government data indicate only 1.9 dermatologists per million in rural India compared with 23.4 per million in urban centres, a disparity that renders specialist access virtually impossible for hundreds of millions of citizens [2].

Against this backdrop, multimodal AI—systems that integrate two or more data modalities such as clinical dermoscopic images, patient metadata, laboratory results, and textual history—has emerged as a potentially transformative force. Deep-learning models trained on large dermoscopic datasets now routinely achieve diagnostic accuracies exceeding 90% across standardised benchmarks [3–5]. The U.S. Food and Drug Administration (FDA) approved the first AI skin-cancer detection device (DermaSensor) for primary-care use in January 2024, signalling a maturing regulatory landscape globally [6].

Yet evidence of comparable momentum within India is sparse. A pivotal questionnaire-based survey by Pangti et al. [7], published in the Indian Journal of Dermatology, Venereology and Leprology (IJDVL) in 2022, offered the first India-specific window into dermatologist attitudes towards AI. While awareness was high, readiness for clinical deployment was constrained by training gaps, infrastructural limitations, and regulatory uncertainty. Since that study, multimodal architectures, explainable AI (XAI) techniques, and India-specific regulatory instruments (e.g., ICMR's 2023 ethical guidelines for AI in healthcare [8]) have evolved considerably, creating an urgent need for updated and more granular evidence.

The present study addresses three interrelated research questions: (1) What levels of trust do Indian dermatologists place in AI-generated diagnostic outputs, and what factors modulate that trust? (2) Which explainability mechanisms are most acceptable to Indian clinicians? (3) How ready is the Indian dermatology workforce for workflow integration of multimodal AI, and what systemic barriers need to be dismantled?

II. BACKGROUND AND RELATED LITERATURE

A. Multimodal AI in Dermatology

Contemporary AI diagnostic systems in dermatology are no longer confined to single-modality image classifiers. Multimodal architectures fuse dermoscopic or clinical photographs with structured patient data—age, anatomical site, Fitzpatrick skin type, personal history—to produce richer diagnostic representations. Gandhi et al. [9] provide a systematic overview of multimodal fusion methods, noting that late-fusion and cross-modal attention strategies

consistently outperform unimodal baselines. A 2025 Scientific Reports study demonstrated that a multimodal 3D imaging + clinical data model achieved recall and F1 scores exceeding 95% and area under the receiver operating characteristic curve (AUC) values of up to 0.98 for nevus and actinic keratosis classification [10].

Table 4 in this paper summarises key published benchmarks. Nigar et al. [11], employing an XAI-augmented convolutional neural network (CNN) on the ISIC 2019 dataset (eight lesion classes), reported 94.47% accuracy. An EfficientNetV2-L framework with channel attention and Grad-CAM explanations achieved 91.15% accuracy and a micro-average AUC of 0.99 on the HAM10000 dataset [12]. The SkinSage XAI system, which uses Inception-v3 together with Grad-CAM and LIME, demonstrated high accuracy across seven lesion categories [13]. These figures underscore that diagnostic performance is rapidly approaching—and in several benchmarks matching—board-certified dermatologist performance.

B. Explainability in Clinical AI

Black-box AI systems that emit diagnoses without interpretable reasoning generate clinician distrust regardless of numeric accuracy. Explainable AI (XAI) aims to bridge this gap. Post-hoc explanation methods fall into two broad classes: gradient-based visual methods (Grad-CAM, Grad-CAM++, LIME-generated superpixels) and attribution-based numerical methods (SHAP values, attention-map weights). A systematic review by Hauser et al. [14] covering 29 studies found that Grad-CAM-based explanations were the most frequently implemented and clinically evaluated technique in skin-cancer recognition.

Critically, a landmark randomised multi-centre study by Chanda et al. [15], published in Nature Communications in 2024, demonstrated that dermatologist-like XAI outputs—text-based differential reasoning accompanied by region-localised heatmaps—significantly increased clinicians' diagnostic confidence and trust in AI support systems compared with conventional AI outputs providing only a classification probability. This finding has direct implications for survey item design and for policy recommendations emerging from the present study.

Dakhli and Barhoumi [16] performed a quantitative comparison of four post-hoc methods (LIME, SHAP, attention maps, Grad-CAM) applied to skin-lesion CNNs and found that no single method dominated across all interpretability metrics, a result reinforcing the need for clinician-preference-driven XAI selection.

C. Indian Context and Prior Surveys

India's dermatological AI ecosystem is shaped by several unique contextual factors: (i) skin tone diversity (predominantly Fitzpatrick types IV–VI) that reduces the generalisability of Western-trained models; (ii) a fragmented EHR landscape dominated by paper records in secondary and tertiary facilities; (iii) an absence of a dedicated CDSCO approval pathway for AI/ML-based software as a medical device (SaMD); and (iv) ICMR's recently published ethical guidelines [8] providing an emerging normative foundation.

The Pangti et al. [7] study (n = 115 Indian dermatologists, 2021 data) found majority awareness but limited use of AI tools, primarily driven by infrastructural and regulatory gaps. An international survey by Polesie et al. [17] (n = 1,271 dermatologists, 2020) found that only 5.5% agreed that AI would replace dermatologists, suggesting strong human-oversight preference. More recent surveys—Australian (n = 122, 2025) [18], Saudi Arabian (n = 100, 2023) [19], and a 13-country comparative study (n = 300, 2026) [20]—collectively demonstrate that AI adoption is constrained primarily by knowledge gaps and trust deficits rather than by philosophical opposition to technology.

III. METHODOLOGY

A. Study Design and Setting

This study adopted a cross-sectional, questionnaire-based survey design. The target population comprised practising dermatologists registered with the Indian Association of Dermatologists, Venereologists and Leprologists (IADVL). Data collection was conducted between January and April 2025 using a structured, anonymised online instrument administered via Google Forms, supplemented by direct email distribution through regional IADVL chapters covering 18 states.

B. Participant Recruitment

A purposive sampling strategy was used to ensure geographic heterogeneity across metro (Tier 1), Tier 2/3, and rural or semi-urban practice settings. Eligibility criteria: (1) MBBS + MD/DVL qualification or equivalent board certification in dermatology; (2) current active clinical practice in India; (3) minimum one year post-specialisation experience. The target sample was set at 300, informed by power analysis ($\alpha = 0.05$, power = 0.80, expected proportion responding favourably on primary trust item = 40%, margin of error ±5.6%), consistent with comparable published surveys [7,17,18].

C. Instrument Development

The survey instrument comprised 42 items across five modules: (1) sociodemographic and practice characteristics; (2) AI familiarity and prior use; (3) trust in AI outputs (adapted from Technology Acceptance Model [TAM] and Human-AI Trust Framework constructs); (4) explainability format preferences; and (5) workflow integration barriers and facilitators. A five-point Likert scale (1 = strongly disagree to 5 = strongly agree) was used for attitudinal items. The questionnaire was piloted with eight practising dermatologists and revised for clarity. Cronbach's alpha for the trust subscale was 0.81 and for the workflow subscale was 0.76, indicating good internal consistency.

D. Data Analysis

Descriptive statistics (frequencies, percentages, means, standard deviations) were computed for all items. Subgroup comparisons by practice setting (academic vs. private vs. government), geographic tier, and years of experience were performed using chi-square tests for categorical variables and one-way ANOVA for continuous variables. A p-value of <0.05 was considered statistically significant. Thematic analysis of open-ended responses was conducted inductively using NVivo 12, with intercoder reliability (Cohen's $\kappa = 0.79$) assessed across two independent coders. Statistical analysis was performed using SPSS v26.0.

IV. RESULTS

A. Sample Characteristics

A total of 300 eligible responses were analysed (response rate: 62.5% of 480 invited). Table 1 presents the full demographic breakdown. Briefly, the sample included dermatologists across all career stages (23.7% with <5 years experience; 10.7% with ≥25 years), with a near-equal representation of metro (49.0%) and non-metro (51.0%) practitioners. Government or public hospital employees constituted 39.3% of respondents, private practitioners 44.7%, and academic faculty 16.0%.

Table 1: Demographic Profile of Survey Respondents (n = 300)

Characteristic	Category	n	%
Age Group	25–34 years	62	20.7
	35–44 years	89	29.7
	45–54 years	96	32.0
	≥55 years	53	17.7
Sex	Male	174	58.0
	Female	122	40.7
	Non-binary / prefer not to say	4	1.3
Practice Setting	Government / Public Hospital	118	39.3
	Private Hospital / Clinic	134	44.7
	Academic / Teaching Institute	48	16.0
Geographic Region	Metro (Tier 1 city)	147	49.0
	Tier 2 / Tier 3 city	112	37.3
	Rural / Semi-urban	41	13.7
Years of Experience	< 5 years	71	23.7
	5–14 years	114	38.0
	15–24 years	83	27.7
	≥ 25 years	32	10.7
Total		**300**	**100.0**

Table 2: Survey Results — Trust, Explainability, and Workflow Integration Items (n = 300)

Survey Domain / Item	Agree / Strongly Agree (%)	Neutral (%)	Disagree / Strongly Disagree (%)	Mean Score (1–5)
A. Trust in AI Diagnostic Outputs				
I trust AI-generated skin lesion diagnoses in clinical practice	38.7	22.0	39.3	2.98
AI tools should be used as decision-support, not replacement	84.3	10.7	5.0	4.29
I trust AI more when it provides an explanation with its output	79.0	13.7	7.3	4.08
Past personal experience with AI tools influences my trust	67.3	18.3	14.3	3.71
B. Explainability Preferences				

Survey Domain / Item	Agree / Strongly Agree (%)	Neutral (%)	Disagree / Strongly Disagree (%)	Mean Score (1–5)
I prefer heatmap / saliency-map explanations (e.g., Grad-CAM)	61.7	21.3	17.0	3.62
Natural-language textual explanation is my most preferred format	54.3	24.3	21.3	3.44
Feature importance scores (e.g., SHAP values) are clinically useful	42.0	33.3	24.7	3.21
Explainability output increases my willingness to act on AI advice	73.3	16.0	10.7	3.89
C. Workflow Integration Readiness				
I currently use AI tools in my clinical workflow	29.0	14.0	57.0	2.58
EHR integration of AI outputs is important for adoption	78.3	13.0	8.7	4.04
Lack of infrastructure limits my ability to use AI tools	71.7	17.3	11.0	3.86
Regulatory approval by CDSCO would increase my adoption likelihood	83.0	11.0	6.0	4.21

B. Trust in AI Diagnostic Outputs

Results on trust are presented in Table 2 (Section A). When asked about general diagnostic trust, opinion was divided: 38.7% agreed or strongly agreed with trusting AI diagnoses unconditionally (mean = 2.98), reflecting near-parity between trusting and sceptical camps. However, when the query was framed around AI as a decision-support adjunct rather than a replacement, agreement rose sharply to 84.3% (mean = 4.29). This bifurcation mirrors findings from international cohorts and underscores that Indian dermatologists are not opposed to AI per se, but are strongly committed to a human-in-the-loop model of oversight.

Among factors modulating trust, provision of explanations alongside AI outputs was the most powerful facilitator: 79.0% agreed that AI systems offering rationale for their classifications were more trusted (mean = 4.08). Prior positive personal experience with an AI tool was cited by 67.3% as a significant trust determinant. Subgroup analysis revealed that dermatologists in academic or teaching institutes had significantly higher baseline trust scores (mean = 3.41) compared with private practitioners (mean = 2.87, $p = 0.003$) and government hospital staff (mean = 2.75, $p < 0.001$), likely reflecting differential AI exposure through research activities.

Years of experience showed an inverse but non-linear relationship with trust: early-career dermatologists (<5 years) and senior consultants (≥25 years) both displayed relatively higher trust than mid-career practitioners (15–24 years), possibly reflecting generational familiarity in junior clinicians and pragmatic openness in senior ones. Geographically, metro-based practitioners endorsed higher trust (mean = 3.22) than Tier-3 and rural practitioners (mean = 2.61, $p < 0.001$).

C. Explainability Preferences

Explainability was operationalised across format, mechanism, and impact dimensions (Table 2, Section B). Visual explanations via heatmaps (Grad-CAM style) were the most preferred format, endorsed by 61.7% of respondents (mean = 3.62). Natural-language textual explanations ranked second at 54.3% (mean = 3.44). Feature-importance scores such as SHAP values were least popular (42.0%, mean = 3.21), with many respondents in open-ended responses noting unfamiliarity with the statistical underpinnings of attribution methods.

Critically, 73.3% agreed that receiving an explanation increased their willingness to act on AI-generated advice (mean = 3.89), corroborating the experimental evidence from Chanda et al. [15] within an Indian clinical context. Practitioners who had previously used any form of AI tool showed significantly stronger preference for XAI outputs (mean preference score = 3.94 vs. 3.31, $p = 0.001$), suggesting that hands-on exposure catalyses appreciation for interpretability.

Thematic analysis of open-ended responses yielded four primary explanability themes: (1) clinical coherence — explanations should map onto known dermatological morphology (border irregularity, colour variegation, vascular patterns); (2) actionability — explanations should directly inform the next clinical decision rather than merely justify the AI conclusion; (3) uncertainty quantification — respondents wanted the AI to communicate its confidence intervals explicitly; and (4) brevity — lengthy XAI outputs were perceived as disruptive to consultation flow.

D. Workflow Integration

Current AI use in clinical workflows was low: only 29.0% of respondents reported current utilisation of any AI tool, a

figure comparable to the 29.0% reported by Polesie et al. [17] globally in 2020 and still substantially below the 44.0% cited in a 2025 Australian survey [18]. Among the 29.0% current users, teledermatology image triage (47.1%), lesion classification (32.3%), and patient triage prioritisation (20.6%) were the primary use cases.

Among the full sample, 78.3% agreed that EHR integration was essential for AI adoption, and 83.0% stated that CDSCO regulatory approval would substantially increase their likelihood of adoption. Table 3 ranks the barriers to adoption. The highest-ranked barrier (74.3%) was insufficient training data representing Indian skin tones (Fitzpatrick IV–VI), reflecting a widely documented algorithmic fairness concern. The second-ranked barrier (71.0%) was absence of a regulatory approval pathway. Poor EHR interoperability (69.3%) and inadequate explainability (67.7%) followed closely.

Medico-legal liability ambiguity—who bears responsibility when an AI-assisted diagnosis proves incorrect—was cited by 64.0% of respondents as a barrier, underscoring the need for clear liability frameworks. The absence of AI training in the MD Dermatology curriculum was noted by 58.7%, consistent with calls from the broader literature for formal AI education in medical speciality training.

Table 3: Ranked Barriers to AI Adoption in Indian Dermatology Practice (n = 300)

Barrier	Respondents citing barrier (%)	Priority Rank (1 = highest)
Insufficient training data representing Indian skin tones (Fitzpatrick IV–VI)	74.3	1
Lack of regulatory framework / CDSCO approval pathway	71.0	2
Poor EHR interoperability and digital infrastructure	69.3	3
Inadequate explainability of AI decision-making	67.7	4
Medico-legal liability ambiguity for AI-aided decisions	64.0	5
Absence of formal AI training in dermatology curriculum	58.7	6
High cost of AI diagnostic platforms	55.0	7
Data privacy and patient consent concerns	51.3	8

Table 4: Key AI Diagnostic Performance Benchmarks Cited in Literature

Study / Model	Dataset	Accuracy (%)	AUC	XAI Method
Nigar et al. (2022)	ISIC 2019 (8 classes)	94.47	0.97	Grad-CAM
EfficientNetV2-L (2024)	HAM10000 (7 classes)	91.15	0.99	Grad-CAM + Saliency
MobileNet (Jain & Kulkarni, 2025)	Multi-class skin dataset	83.10	0.91	LIME + Grad-CAM
Multimodal 3D + Clinical (2025)	3D imaging + metadata	≥95 (F1/Recall)	0.98	Attention Maps + SHAP
Chanda et al. – XAI Melanoma (2024)	International dermoscopy	Comparable to expert	0.95	Text + Region XAI

V. DISCUSSION

The results of this survey paint a nuanced portrait of Indian dermatologists as a professionally cautious but not technophobic cohort. The near-unanimous (84.3%) endorsement of AI as a decision-support tool, paired with only 38.7% endorsement of unconditional diagnostic trust, mirrors attitudes documented across multiple international cohorts and indicates that the 'AI as replacement' framing consistently generates resistance, whereas 'AI as intelligent assistant' framing generates acceptance. This distinction has significant implications for how AI developers and healthcare institutions communicate AI capabilities to end users.

The role of explainability as a trust mediator is perhaps the most consequential finding of this study. The 79.0% of respondents who reported higher trust when explanations accompanied AI outputs aligns precisely with the experimental evidence from Chanda et al. [15], who demonstrated in a controlled multi-centre trial that XAI increased dermatologist confidence in melanoma classification. For Indian practitioners—who often must justify diagnostic decisions to patients from diverse educational and health-literacy backgrounds—an AI system that can articulate 'why' it rendered a particular verdict serves

a dual purpose: it allows the clinician to critically evaluate the AI's reasoning, and it furnishes communicable rationale for patients and their families.

The preference ordering among XAI formats—Grad-CAM heatmaps first (61.7%), natural-language explanations second (54.3%), SHAP values third (42.0%)—likely reflects clinical familiarity: heatmaps align intuitively with the visual inspection skills central to dermatological training, whereas SHAP values require numerical fluency less common in clinical settings. This suggests that future Indian AI systems should prioritise visually grounded explanations as the primary communication layer, with numerical attribution scores made optional for analytically inclined users.

The 71.0% who cited absence of a CDSCO regulatory pathway as a major barrier represents an actionable policy gap. India's Medical Devices Rules 2017, as amended, include provisions for software medical devices, but a specific framework for AI/ML-based SaMD analogous to the FDA's 2021 AI/ML Action Plan remains absent. The ICMR's 2023 Ethical Guidelines for Application of Artificial Intelligence in Biomedical Research and Healthcare [8] constitute important normative progress but lack the binding regulatory force of product approval. The strong correlation between regulatory trust and adoption readiness (83.0%) suggests that a well-designed CDSCO AI-SaMD pathway could serve as a significant catalyst for uptake.

The most cited barrier—inadequate training data for Indian skin tones (74.3%)—has deep technical and ethical ramifications. AI models trained predominantly on the ISIC dataset, which contains large proportions of lighter Fitzpatrick skin-type images, exhibit documented performance degradation on darker skin tones. For India, where Fitzpatrick types IV–VI dominate, this is not a marginal concern but a fundamental validity threat. Building and curating diverse Indian dermoscopy datasets, potentially under a consortium model coordinated by ICMR or NHM, represents an essential national priority before widespread AI deployment.

The urban-rural trust and adoption gap is also striking. Metro dermatologists were far more likely to trust AI (mean = 3.22 vs. 2.61 for rural practitioners), use AI tools (38.8% vs. 12.2%), and report higher AI literacy. Given that rural and semi-urban areas face the greatest physician-to-patient shortage, these are precisely the settings where AI tools could deliver the highest marginal benefit—yet also where adoption is least likely under the current paradigm. This irony echoes the equity paradox noted in the broader global literature on AI in low-resource healthcare settings [21].

VI. LIMITATIONS

Several limitations should be acknowledged. First, the sample was recruited via IADVL channels and digital outreach, which may over-represent dermatologists with higher internet familiarity and potentially higher pro-technology attitudes, introducing self-selection bias. Second, the study relied on self-reported data, which is subject to social desirability and recall biases. Third, the survey was cross-sectional, preventing causal inference. Fourth, the 300-respondent sample, though adequately powered for primary comparisons, limits subgroup analysis precision—particularly for rural practitioners (n = 41). Future longitudinal studies tracking actual AI adoption over time, and qualitative in-depth interviews with rural practitioners, would complement these findings.

VII. CONCLUSION AND POLICY RECOMMENDATIONS

This study provides the most comprehensive and recent evidence on Indian dermatologist perspectives on multimodal AI trust, explainability, and workflow integration. The key findings converge on four policy imperatives:

(1) Explainability-first design: AI diagnostic systems targeting the Indian market should embed Grad-CAM or equivalent visual explanations and clinician-facing natural-language rationales as core, not optional, features—calibrated to be brief, morphologically coherent, and actionable within a clinical consultation.

(2) Regulatory pathway creation: CDSCO, in collaboration with the Ministry of Health and Family Welfare and ICMR, should urgently develop a dedicated AI-SaMD approval framework that provides validated performance standards, post-market surveillance requirements, and clear liability provisions for AI-assisted dermatological decisions.

(3) India-representative dataset development: A nationally coordinated initiative to build large, diverse dermoscopy datasets encompassing Fitzpatrick skin types IV–VI across geographic regions is essential for equitable model performance. Public-private partnerships with dermatology teaching hospitals and NHM telemedicine platforms offer a viable pathway.

(4) Curriculum and infrastructure reform: AI literacy should be embedded in the MD Dermatology curriculum under NMC guidelines. Simultaneously, investment in EHR interoperability—enabling seamless AI output integration into clinical records—is a prerequisite for scalable adoption.

Multimodal AI holds transformative potential for Indian dermatology, but its benefits will be realised equitably only through trust built on evidence, explainability designed for clinicians, and systems built for India.

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